Environmental Regulation and the Reallocation of Credit: Evidence from India

Abstract

We ask whether an aspirational environmental regulation; one that is broad, has no market mechanism, and is weakly enforced, can move bank credit, and whether the lender or the borrower drives it. In January 2019, India's National Clean Air Programme (NCAP) designated a set of cities as "non-attainment" based on their history of persistently poor air quality, making firms in these districts regulatory targets. Comparing districts with and without such a city, before and after 2019, we find that bank credit fell by about 10 per cent and new investment by about 16 per cent in regulated districts, even though measured air pollution fell by less than 2 percent, against a target of 20 percent. Using a within-firm, across-bank design, we show the contraction is borrower-driven: exposed banks did not curtail lending, even to polluting firms, while firms borrowed and invested less and shifted activity to unregulated districts. Banks did not charge higher interest rates, even to polluting firms, in regulated districts. Moreover, the effect is unrelated to how vigorously each district implemented the programme, and polluting firms' disclosures reveal rising air-pollution risk while lenders' do not. We argue that firms retreat because they cannot yet price how the rule will eventually bind, and so defer or relocate irreversible investment.

Keywords: Environmental regulation, bank credit, credit reallocation, regulatory uncertainty, India

1 Introduction

Billions of people across the world breathe polluted air. Every year, air pollution kills millions of people worldwide (World Health Organization, 2021, Landrigan et al., 2018). The dirty air negatively affects health (Deryugina et al., 2019, Ebenstein et al., 2017) and lowers labour productivity, which, in turn, depresses firm output and slows aggregate economic growth (Chang et al., 2019, Fu et al., 2021). Therefore, cleaning the air is a central policy challenge for many countries.

Governments respond to pollution with regulation, which, in turn, can impact markets in many ways. A large literature documents that environmental rules alter where firms locate production, how much they invest, and, on what terms and in what quantity, they raise finance (Greenstone, 2002, Bartram et al., 2022). In this paper, we focus on credit market, and ask whether a clean-air programme affects credit markets at all. If it does, who drives the effect: the regulator, the lender, or the borrower? When a government designates a region for tighter pollution control, each of these three agents can move the credit flowing to the firms in this region in different directions.

The regulator's response depends on institutional strength: in advanced economies rules are typically enforced as written, whereas in emerging economies enforcement is often uncertain. The regulator operating where state capacity is low, may enforce nothing (Greenstone and Hanna, 2014, Duflo et al., 2013), but it might act with force if it recognizes polluted air as a crisis (Kapur, 2020). The lender may ration funds to regulated borrowers to avoid regulatory uncertainty, remain indifferent, or channel more toward them to finance a green transition (Ivanov et al., 2024, Kacperczyk and Peydró, 2023). A firm may borrow more to meet the compliance costs the rule imposes (Ryan, 2012, Xu and Kim, 2022), or it can simply carry on, betting the rule never bites[1], or exercise the option to wait by deferring or relocating capital (Bernanke, 1983, Dixit and Pindyck, 1994, Gulen and Ion, 2016). Firm's

[1]For instance, India's 2015 desulphurisation norms for coal power plants were deferred four times, and most plants were ultimately exempted. Times of India - News Article on July 13, 2025.

response also depend on the flexibility of production technology and investment opportunities (Lin et al., 2026). These forces can offset or reinforce one another; hence, the net effect on credit and the identity of the agent behind it can only be settled empirically.

We examine the impact of India's National Clean Air Programme (NCAP) on credit markets. Launched by the Central Pollution Control Board in January 2019, NCAP designated a set of "non-attainment" cities whose particulate concentrations had persistently violated ambient air quality standards and set a target to cut pollution by 20–30% by 2024 relative to 2017 baseline level. Firm operations in non-attainment districts become regulatory targets, while operations outside these districts do not.

Using the Centre for Monitoring Indian Economy's (CMIE) States of India (SoI) database, we compare the overall credit in non-attainment districts with that in other districts of the country before and after the implementation of the NCAP. On the district-year panel from 2015–2023, using a difference-in-differences method with two-way fixed effects, we find that overall bank credit declined 10 per cent in non-attainment districts after NCAP, relative to other districts.

The drop primarily comes from industrial credit, while some credit shifts to agriculture. The results hold when we restrict the control group to neighbouring districts, and, separately, when we restrict it to non-adjacent districts. They are also robust to Covid-19-related lockdown intensity. Year-wise pre-treatment coefficients are indistinguishable from zero and support the absence-of-pre-trends assumption. The plot shows that the credit started falling in treated districts in the year 2019 itself, even though the action plans were finalized in mid-2020 for implementation. However, during the same period, air pollution, measured by PM2.5, dropped by only 1.9 per cent in these districts, well below the target.

Corresponding to the decline in credit, we see a 16.3 per cent decline in the initiation of new capital expenditure projects in the non-attainment districts compared with other districts, and this reduced investment accounts for much of the credit decline, while the

reverse, credit driving investment, finds no support. These results raise a question: are declines in credit and investment driven by lenders or firms, or by both? We also check whether these results are driven by how vigorously the regulator enforces the regulation.

We establish the answers in three steps. First, we study environmental clearances, the approvals a firm must obtain before starting a project that can harm the environment. We find that firms in treated districts applied for fewer such clearances after NCAP, and this decline in clearances sought accounts for much of the credit decline. We also check if the number of clearances the regulator actually granted is correlated with the drop in credit, and found insignificant results. This evidence points to firms choosing to launch fewer polluting projects, rather than the regulator refusing to approve them.

Second, we test the role of the lender by constructing a firm-bank-year panel using loan-level data (Index of Charges (IoC)) obtained from the Government of India's Ministry of Corporate Affairs (MCA). On this panel, we run a Khwaja and Mian (2008)-style regression that compares how the same firm borrows from banks more and less exposed to treated districts. We find that exposed banks did not significantly curtail lending after NCAP, even to polluting firms. Furthermore, using pooled cross sectional data of credit from Private Circle, we find that lenders did not charge higher interest rate, even to polluting firms, in the regulated districts. We also tested if there is any change in percentage of borrowing out of the current credit limit in districts with higher potential of such borrowing. We find that, among control group, districts with higher potential of such borrowing increased their borrowing. However, no such impact is observed in treated districts. Third, we arrange new investment data from CMIE CapexDx and new borrowing data from MCA Index of Charges in firm-district-year panel. Using this, we follow individual firms across space before and after NCAP, and find that polluting ("brown") firms cut their capital expenditure and borrowing in treated districts by more than five percentage points relative to green firms and shifted both to untreated districts. Firms, in short, walk their money out of the regulated region.

Next, we test if firms are retreating due to the government's enforcement rigour. We find that districts that spent more of their NCAP funds, our proxy for how forcefully the programme was implemented, did not suffer any additional credit decline. These tests show that the credit markets responded to the environmental regulation only via borrower demand, and not via the lender's risk calculation or the government's force.

We hypothesize that firms relocate their borrowing and investment away from non-attainment districts due to their anticipation of future risk of law enforcement and associated costs. Using text analytics on the annual reports of listed firms, we find that polluting firms discuss air-pollution risk far more after NCAP, and in markedly more uncertain and litigious language. Similar analysis of lenders' disclosures shows no effect of NCAP. These findings show that borrowers revise their assessment of the risk, but banks do not. Firms' response in anticipation of regulatory risk is also evident from the coefficient plot of district-wise credit of non-attainment vs other districts. The plot shows that the decline begins upon announcement of NCAP in 2019 itself, even though the action plans were approved later in mid-2020. Firms decide to wait and watch as they face an obligation they cannot yet price. So, they defer or relocate irreversible investment.

Related Literature.— This paper's central contribution is to the literature on environmental regulation and bank credit, which has largely cast the bank as the active agent. A growing body of work shows that as climate policy tightens, lenders reprice or ration credit to carbon-intensive and pollution-exposed borrowers (Ivanov et al., 2024, Kacperczyk and Peydró, 2023, Mueller and Sfrappini, 2025), so that the reallocation of credit is something banks do to firms. This work, however, typically observes the net movement of credit without separating the lender's decision to supply it from the borrower's decision to demand it. We ask: when environmental regulation moves credit, who moves it, the lender or the borrower?

Using a within-firm, across-bank design in the spirit of Khwaja and Mian (2008), we separate out supply side and demand side effects. Banks with greater pre-policy exposure to

regulated districts do not curtail lending after NCAP, not even to polluting firms, and their disclosures reveal no change in perceived risk; the contraction comes from firms borrowing less. Banks not actively responding is in line with Gu et al. (2026), who, studying bank credit and firm emissions in the United States, the European Union, and Denmark, find no evidence of banks actively stewarding the green transition.

Our contribution, however, is not this lender-side null but the decomposition itself. To our knowledge, this paper is the first to separate the demand and supply components of the credit response to environmental regulation and to show that the effect is borrower-driven. This distinction matters because it informs the policymaker about where to target remedies for the regulation's unintended costs. If the lender were withholding credit, a guarantee scheme would work (Bachas et al., 2021), but in this case, the remedy lies in reducing the uncertainty firms face.

Our findings also connect to three further literatures. To the literature on the real effects of environmental regulation and spatial regulatory arbitrage, which since Greenstone (2002) has shown that binding, priceable rules push production toward less-regulated jurisdictions (Ryan, 2012, Walker, 2013, He et al., 2020, 2026), we add that relocation can occur in anticipation of a rule that does not yet bind and cannot yet be priced. To the literature on environmental regulation in developing economies, which ties a rule's effects to the state's capacity to implement it (Muralidharan et al., 2016) and to the monitoring of and incentives facing enforcing officials (Duflo et al., 2013, Kahn et al., 2015, Greenstone et al., 2025, Fisman et al., 2026), we show that a low-capacity state need not enforce a rule at all for it to bite: NCAP moved credit and investment before any enforcement machinery existed, and the effect is unrelated to how vigorously each district implemented the programme. And to the literature on policy uncertainty and irreversible investment (Bernanke, 1983, Dixit and Pindyck, 1994, Bloom, 2009, Baker et al., 2016, Gulen and Ion, 2016, Lin et al., 2026), which infers the option to wait from aggregate uncertainty indices, we contribute a setting where the uncertainty is one regulation, letting us document the firm-level waiting response rather

than infer it.

The remainder of this paper is structured as follows. Section 2 provides an overview of the National Clean Air Program. Section 3 describes the data sources and presents summary statistics. Section 4 outlines our identification strategy. Section 5 reports the empirical results and discusses several mechanisms. Section 6 performs robustness test. Section 7 concludes and outline policy implications.

2 Institutional Setting: National Clean Air Programme

The National Clean Air Programme (NCAP) was launched by India's Central Pollution Control Board in January 2019 as a nationwide effort to address the country's severe ambient air quality crisis. The programme identified "non-attainment cities", which are urban agglomerations where ambient concentrations had persistently exceeded National Ambient Air Quality Standards (NAAQS) thresholds, as the primary regulatory focus. NCAP established a target of reducing PM2.5 and PM10 concentrations by 20–30% by 2024 relative to 2017 baseline levels in these cities. Initially comprising 102 cities, the program was subsequently expanded to 131 cities. Furthermore, National Green Tribunal, a judicial body for environmental protection, ordered these non-attainment cities to prepare city action plan to combat air pollution which would be approved by the Central Pollution Control Board.

A key feature of NCAP is its aspirational and non-binding character. The regulatory framework is organized around three pillars: (i) *mitigation*, encompassing afforestation, clean technology deployment, and sectoral interventions; (ii) *knowledge*, covering expanded monitoring networks, scientific studies, and a national pollution inventory; and (iii) *institutional*, addressing capacity building, public awareness, and community engagement.

Notably, NCAP does not specify quantified emissions reduction targets for individual firms, and does not create any market mechanism. It does not prescribe mandatory com-

pliance deadlines for polluting industrial units. Ganguly et al. (2020) studies NCAP's City Action Plans and find that 74% of action points fall in the "institutional" category, using language like "overseeing," "planning," "proposing," and "investigating." This is in sharp contrast to the well-defined, targeted interventions that characterize the regulations most studied in prior financial economics literature.

3 Data and Summary Statistics

Appendix Table A1 defines every variable used in the analysis and lists its source.

3.1 Credit and Investment Data

Our primary data come from the CMIE States of India database, which provides district-year panel data on total outstanding loans from Scheduled Commercial Banks. We further use the data on the total Industrial, Agricultural, and Personal outstanding credit. These three are the biggest sub components, making up to 80% of the total outstanding credit. This dataset covers all 767 Indian districts over our entire sample period of 2015–2023, resulting in 6072 District-Year observations.

Table 1 reports summary statistics for the main variables used in our analysis. Summary statistics in Appendix Table A2 show that Treated districts had significantly more outstanding bank credit than control group before the policy implementation. This is true for sub components of total credit also. This reflects that treated districts, on average, have higher level of economic activity. However, this is not a problem for our estimation as long as parallel trend holds. Moreover, we also perform a robustness test with a more comparable control group.

We obtain loan-level data on new credit from the Index of Charges dataset of the Ministry of Corporate Affairs (MCA). This has data on the borrowing firm, lending institution, loan

sanction date, loan amount, and lending location for all charge registrations with the Ministry of Corporate Affairs. This dataset allows us to construct the firm-bank-year panel. We also got data of interest rate charged on credit from the Private Circle. This has data on lending and borrowing institutions, and other credit details along with details of interest rate charged. We merged this data with Index of Charges dataset to get pooled cross sectional data on interest rate charged in districts across India.

To check for potential mechanisms of the reduction in outstanding credit, we used data on district level new investments from CMIE States of India. To check the role of environmental clearances, we got the yearly data on environmental clearances sought and received from CMIE CapexDx. We also used the investment announcements by firms from this dataset. We built firm-district-year panel of investment announcements to study spatial reallocation of investment at the firm level.

3.2 Air Pollution Data

We use daily PM2.5 estimates at 10 km spatial resolution from Kawano et al. (2025). They constructed this dataset using a machine-learning model trained on satellite remote sensing inputs and has data for the period 2005–2023. This provides more granular data and covers more area than India's ground-based monitoring network. We aggregate these estimates at the district-year level for use in our analysis.

3.3 Additional Data

To understand what companies are discussing regarding the impact of NCAP on their business, we read Annual reports of Indian listed companies from the Prime Infobase. We use these to study whether firm-level disclosure of air-pollution-related risks changed differentially after NCAP for polluting versus non-polluting firms.

NCAP was announced in 2019 which was also the year when Covid 19 pandemic started. So, to control for Covid 19, we used the data on average percentage change in transit visits to workplace for 2020 and 2021 from Google Mobility Index. Districts with above median level of mobility declines are classified as high-COVID districts.

We constructed a proxy of implementation intensity of this regulation from district-wise NCAP fund utilization data from the Prana Platform of the Central Pollution Control Board. Geographic boundary data come from India Post's pincode-to-district concordance and official shape files.

4 Empirical Strategy

We first establish that NCAP moved credit and investment away from treated districts (Section 4.1), then ask whether the movement runs through investment and clearances (Section 4.2), whether the firm or the bank drives it (Sections 4.3–4.4), whether disclosures reveal a change in perceived risk (Section 4.5), and whether enforcement rigour explains it (Section 4.6). Throughout, $Treat_d$ equals one for districts containing an NCAP non-attainment city, $Post_t$ equals one for 2019 onwards, and $Brown_i$ equals one for firms in polluting sectors.

4.1 Baseline: District-Level Difference-in-Differences

We estimate a two-way fixed-effects difference-in-differences (DiD) on district-year data for 2015–2023, comparing treated districts (those with an NCAP non-attainment city) to all others, before and after 2019:

$$Y_{dt} = \alpha + \beta(Treat_d \times Post_t) + \gamma_d + \delta_t + u_{dt} \tag{1}$$

where Y_{dt} is the outcome in district d and year t. District fixed effects γ_d absorb the $Treat_d$ level and year fixed effects δ_t absorb the $Post_t$ level, so we estimate only their interaction. Standard errors are clustered at the district level. The coefficient β measures the change in credit in treated relative to control districts after NCAP.

4.2 Does Investment Drive Credit, or Credit Drive Investment?

Credit and new investment both fall in treated districts, but their totals cannot say which drives which: fewer projects could dry up borrowing, or tighter credit could choke off projects. We test both directions with the same triple difference run each way:

$$A_{dt} = \alpha + \beta(Treat_d \times Post_t) + \lambda(Treat_d \times Post_t \times B_{d,t-1}) + \Gamma\, W_{dt} + \gamma_d + \delta_t + u_{dt} \qquad (2)$$

where the pair (A, B) is either (credit, investment) or (investment, credit), both in logs, and W_{dt} collects the constituent terms. The coefficient λ asks whether, in treated districts after NCAP, the outcome moves with the lagged level of the other variable. We lag B by one year because financing follows a project announcement, and to avoid mechanically relating the two within a year. We repeat the test with environmental clearances sought and received in place of investment.

4.3 Firm-Level Spatial Reallocation

To see the firm's hand directly, we build a firm-district-year panel of capital expenditure and, separately, of new borrowing, and estimate:

$$Y_{idt} = \alpha + \beta(Treat_d \times Post_t) + \theta_{it} + \gamma_d + \varepsilon_{idt} \qquad (3)$$

where Y_{idt} is log capital expenditure or an investment indicator (or, in the borrowing version, log credit or a credit indicator). The firm-year fixed effect θ_{it} absorbs everything about a firm in a given year, so identification comes only from a firm splitting activity across a treated and an untreated district in the same year. β measures how much a firm shifts activity out of treated districts after NCAP.

To test whether this is concentrated in the most exposed firms, we classify firms as polluting ("brown") or green using IPCC sectoral definitions mapped to CMIE industries following Fisman et al. (2026), and add a triple interaction:

$$Y_{idt} = \alpha + \beta(Treat_d \times Post_t) + \eta(Treat_d \times Brown_i) + \lambda(Treat_d \times Post_t \times Brown_i) + \theta_{it} + \gamma_d + \varepsilon_{idt} \tag{4}$$

Here θ_{it} absorbs $Brown_i$ and its interaction with $Post_t$, and γ_d absorbs $Treat_d$; we retain the un-absorbed $Treat_d \times Brown_i$ term. A negative λ says brown firms move capital and borrowing out of treated districts by more than green firms.

4.4 Supply Side: Isolating the Bank's Decision

A firm borrowing less and a bank lending less look identical in district totals. To separate them, we use a Khwaja and Mian (2008)-style design on a firm-bank-year panel from the MCA Index of Charges: for a firm borrowing from two banks in the same year, does the one more exposed to treated districts before NCAP lend it less? We measure exposure, $Exposure_b$, as the share of a bank's 2005–2018 lending directed to treated districts, and estimate:

$$Y_{fbt} = \alpha + \delta(Post_t \times Exposure_b) + \phi_{ft} + \psi_b + \varepsilon_{fbt} \tag{5}$$

where Y_{fbt} is log credit (or a credit indicator) from bank b to firm f, the firm-year fixed effect ϕ_{ft} absorbs the firm's entire demand, and ψ_b is a bank fixed effect. A null δ means more-exposed banks did not curtail lending to the same firm after NCAP. We repeat the

test interacting exposure with $Brown_f$.

4.5 Firm Expectations: Textual Evidence from Annual Reports

If firms pull back in anticipation of the rule, their disclosures should show it. On a firm-year panel of annual reports (2015–2023), we measure mentions of air-pollution terms and the share of words in those passages that are uncertain or litigious (Loughran and McDonald, 2011), and estimate:

$$R_{it} = \alpha + \beta(G_i \times Post_t) + \gamma_i + \delta_t + \varepsilon_{it} \tag{6}$$

where R_{it} is either outcome for firm i in year t, and γ_i and δ_t are firm and year fixed effects that absorb the group indicator G_i and $Post_t$ on their own. We run it with two group indicators in turn: $Brown_i$, testing whether polluting firms discuss pollution risk more, and in more uncertain, litigious terms, after NCAP; and $Lender_i$, testing whether lenders' disclosures reveal any parallel change.

4.6 Implementation Intensity

Finally, we test whether the credit decline merely tracks how forcefully each district implemented NCAP. Using fund utilisation (the share of allocated funds a district had spent) as a proxy for enforcement rigour, we estimate across treated districts:

$$Y_{dt} = \alpha + \beta(Post_t \times FundUtil_d) + \gamma_d + \delta_t + u_{dt} \tag{7}$$

with $FundUtil_d$ also entered as an above-median indicator. A null β means the effect does not run through how vigorously the programme was enforced.

5 Results and discussion

5.1 Main Result

Table 2 shows the impact of National Clean Air Programme (NCAP) on outstanding bank credit of the Non-attainment (treated) districts compared to attainment (control) districts. We find in column (1) that PM2.5 has reduced by roughly 2 percent in treated districts compared to control districts after the NCAP. However, outstanding credit in column (2) has dropped by more than 10 percent in the treated districts . When we break credit into their sub-components in columns (3)-(5) , we find that the proportion of industrial credit in total credit has declined. Interestingly, the proportion of agricultural credit has increased. We find no impact on Personal credit.

Together, this shows that NCAP adversely impacted the treated districts as it suffered a decline in credit. Moreover, the impact is concentrated in the industrial sector. This is consistent with the hypothesis that industrial sector is more exposed to air pollution control regulatory risk.

The DiD estimator in equation (1) identifies the causal effect of NCAP designation under the parallel trends assumption. This assumption states that, in the absence of NCAP, credit outcomes in treated and control districts would have evolved along parallel trajectories. We plot the coefficients plot in Figure 1 to check parallel trend. We find that treatment coefficients for 2015–2018 are statistically indistinguishable from zero, showing that the parallel trends assumption holds. The credit decline begins sharply in 2019, the year of NCAP's launch, and persists through 2023.

5.2 Mechanism

Previous literature has shown that an increase in regulatory risk leads to a decline in investment by the firms as firms either reallocate their investment to unregulated regions or, due to increased uncertainty, they adopt a strategy of "wait and watch" (Dixit and Pindyck, 1994, Bernanke, 1983). So we estimated the impact of NCAP on investment and checked if this explains the drop in credit in Non-attainment (treated) districts.

First, we used the difference-in-difference specification in equation (1) to estimate the impact of NCAP on new investment in a district. Then, we used the triple difference-in-difference specification in equation (2) to test if the change in new investment explains the drop in credit in Non-attainment districts.

Table 3 reports the effect of NCAP on district-level new investment (column 1) and on the credit-investment relationship (column 2). In column (1), we see that new investment declined by roughly 16 percent in Non-attainment districts.

Column (2) examines whether lag of investment explains the change in credit in a district. The coefficient on triple interaction term is positive and significant, showing that higher level of past investment is associated with higher level of credit in treated districts after regulation. Since, column (1) shows that the new investment has declined in treated districts, this reduced level of new investment explains the drop in credit in those districts. We rule out the possibility of reverse causality between investment and credit by finding that lag of credit does not explain change in investment in a district.

Environmental clearances. In India, firm has to get environmental clearance from regulator for projects that can significantly harm the environment. Since environmental regulation targets activities that harm the environment, NCAP could impact the credit through the environmental clearance channel. To test this mechanism, we use the difference-in-difference specification in equation (1) to estimate the impact of NCAP on environmental clearances.

We also use the triple difference-in-difference specification in equation (2) to test if the change in environmental clearances explain the drop in credit in the Non-attainment districts.

We looked at the impact of NCAP on both Environmental clearance sought and clearances received. In column (1) of Table 4, we see that firms are seeking less number of environmental clearances in the treated districts compared to control districts after NCAP. This indicates that firms are reducing the number of new projects that need environmental clearances. In other words, firms are reducing investments, especially those that can harm the environment, in the treated districts. Moreover, we see in column (2) that the number of environmental clearance sought is positively associated with credit in treated districts after the regulation. However, since there is a decline in number of clearances sought in column (1), this provides evidence that decline in environmental clearance explains the drop in credit in treated districts post regulation.

Similarly, in column (3) , we see that firms are receiving less environmental clearances from regulators in the treated district. This is not surprising given the fact that they are seeking less clearance. But, the triple interaction result in column (4) shows change in number of clearances received is not associated with change in credit in the treated districts. This rules out the possibility that credit decline is driven by regulators giving less clearance in treated districts. Together, the result on environmental clearance supports the hypothesis that drop in credit is driven by demand side adjustment by firms seeking less clearances and not supply of less clearances by the regulator.

5.3 Firm Level analysis and Heterogeneity

To understand the response of firms to NCAP in more detail, we look at the Firm-district-year panel of their capital expenditure. We use the difference-in-difference specification with Firm $\times$ Year Fixed effects in equation (3) so that identification comes from variation across districts within the same firm in the same year. Column (1)-(2) in Appendix Table A3 shows

that firms reduced their capital expenditure by more than percent in the treated districts compared to control districts after regulation. Similar result hold when we use investment dummy as the dependent variable in column (3)-(4). Investment dummy takes value one if a firm makes an investment in a particular district-year pair and zero otherwise.

To estimate the heterogeneous impact of NCAP on polluting versus non polluting firms. To classify firms into these two categories, we used the definition of brown and green sectors from Intergovernmental Panel on Climate Change (IPCC). IPCC gives the broad industrial category names for brown and green sectors. We hand-mapped that to the more granular description of industry names in CMIE CapexDx dataset. This is a similar approach that has been followed for categorization of brown firms by Fisman et al. (2026).

Following this, using the triple difference-in-difference in equation (4), in column (1)-(2) in Table 5, we find that that polluting (Brown) firms reduced their CapEx by more than 5 percent compared to non-polluting firms. Similar result hold when we use investment dummy as the dependent variable in column (3)-(4). This is consistent with the hypothesis that the polluting firms face more regulatory risk of pollution regulation than non-polluting firms. This evidence also establishes that firms with operations with multiple district redirected investment away from their treated district locations after NCAP. This spatial reallocation is stronger by polluting firms.

We also explored the decision of a firm to borrow in the treated district after NCAP. We used the same triple difference-in-difference specification as before (equation 4) with Firm $\times$ Year Fixed effect. So, the identification comes from variation across districts within the same firm in the same year. We see in column (1)-(2) of Table 6 that polluting firms have sharply reduced their borrowing in the treated districts compared to green firms after NCAP. Similar result hold when we use credit dummy as the dependent variable in column (3)-(4). Credit dummy takes value one if a firm receives any credit in a particular district-year pair and zero otherwise. This supports the spatial reallocation hypothesis wherein polluting firms are

shifting their financial activities from treated to untreated districts because of their greater exposure to regulatory risk.

5.4 Supply Channel: Ruling Out Supply side mechanism

To test the supply side impact of NCAP on bank credit,i.e, to check if banks are lending less to polluting firms, we use Khwaja and Mian (2008) type specification in a Firm-Bank-Year panel of credit data. First, we calculate the exposure of each bank to treated districts before the regulation. For this, we construct a ratio of the total credit given by a bank in the treated district and total credit given by that bank in the entire country in the last 10 years, i.e, between the period 2008–2018. This gives the pre-policy exposure of each bank to NCAP. We call this variable "Exposure". Then, we use the difference-in-difference specification in equation (5) where our main variable of interest is the coefficient on the interaction of Exposure and Post variables. This coefficient will estimate the difference between lending by banks with more pre-policy exposure to treated districts and those with less exposure. Column (1)-(2) in Table 7 shows that banks exposure does not have significant impact on lending to firms. Column (1)-(2) in Appendix Table A4 show the exposure does not matter for lending to polluting firms also. Similar results hold for Credit dummy also in both tables. Together, these results rule out out a supply-side channel of credit reallocation from treated to control districts after the NCAP.

To test another potential supply side channel of the impact, we tested if banks are charging higher interest rates on loans given in the treated districts. We use specification similar to Equation 3, with a different set of fixed effects, on the pooled cross sectional data of interest rate. Column (1) in Table 8 shows that there is no significant change in the interest rate on credit in regulated districts compared to unregulated districts after the regulation. This is true for interest rates charged in the subsample of Brown and Green firms also in Column (2) and (3) respectively. To test the impact of regulation on brown firms in the

regulated districts, we use specification similar to Equation 4, with a different sets of fixed effects, on this dataset. Again, from the coefficient on the triple interaction term in column (4)-(5), we find no significant impact on interest rate. Together, these results rule out out a supply-side channel of higher interest rate charged on credits in regulated districts after the NCAP.

We also studied Credit limit utilization in districts to separate demand and supply side effect of NCAP regulation. Greenwald et al. (2025) finds that firms increased their credit utilization by drawing heavily from their standing credit line facility after the Covid-19 Shock. Consequently, banks that experienced larger credit line drawdowns restricted term lending more. Following this line of inquiry, we tested if districts with high potential of borrowing from their available credit limit, i.e, districts with below median level of ratio of credit outstanding to total credit limit before the NCAP regulation, increases their borrowing after this intervention.

We did not find any such effect in Table A5. The coefficient on the triple interaction term in column (1) shows that the borrowing percentage, i.e, the percentage of outstanding credit out of total credit limit, actually decreased in districts with high potential of drawing from their available credit limit compared to districts with low potential of such borrowing. Moreover, the subsample analysis in column (2)-(3) show that while there is no change in borrowing percentage in high potential districts among the treated districts, there is higher utilization of borrowing out of credit limit in the corresponding case of control districts. This is consistent with the evidence that firms are moving out their economic activities from treated to control districts after the NCAP. Together, these evidences strengthen the hypothesis that the impact of this regulation on bank credit is driven by demand side, not by supply side.

5.5 Firm Expectations: Textual Evidence from Annual Reports

To have a better understanding of how firms are factoring in this regulation, we looked at their discussion related to NCAP in their annual reports. To do this, first, we made a dictionary of 100 words that contains words that related to air pollution regulation like air pollution, pollution regulation etc. This gives us the number of times pollution related terms are used in tan annual report. This gives us the pooled cross section of count of words from year 2015–2023. Then, we used Loughran and McDonald (2011) dictionary to classify the mention of these words into the sentiments they represent. Loughran and McDonald (2011) dictionary classifies words into different categories that convey their underlying sentiment.

Finally, we use the difference-in-difference specification in equation (6) to check the mention and sentiment of pollution related words after the NCAP. We find in column (1) of Table 9 that polluting firms are mentioning air pollution related words more than non polluting firms after NCAP. Furthermore , to check the sentiment of these mentioned words, we take the total words that fall under the categories of Uncertainty and Litigious risk by Loughran and McDonald (2011) dictionary. We divide this sum by the total words written in the annual reports. This ratio gives us the proportion of total words that correspond to Uncertainty and Litigious risk categories. We call this variable broadly as *Risk sentiments*. Column (2) shows that the mention of *Risk sentiments* words also increased significantly after the NCAP. Importantly, when we did this same analysis on the subsample of lending institutions only, the results in column (3)-(4) are insignificant. Appendix Figure A1 plots the pattern over time, showing that air-pollution mentions in polluting firms' reports rise around NCAP's launch relative to other firms.

Together, these results show that the mention of air pollution related words by polluting industry firms increased after the NCAP. Among these firms, the mention of *Risk sentiments* words by polluting firms also increased. However, there is no such significant change in the case of lending institutions. This is consistent with the hypothesis that NCAP has adverse

impact on polluting firms but lenders are not perceiving any significant change in risk. This strengthens the result that the impact of NCAP is not driven by supply side, but is primarily a demand side effect.

5.6 Implementation Intensity of Regulator

A potential alternative mechanism of credit decline in treated districts could be due to intensity of regulatory implementation. In other words, districts with more stringent implementation of regulation districts might have suffered a greater decline in bank credit. To test this mechanism, we use NCAP fund utilization as a proxy of regulatory implementation intensity. Fund utilization is the percent of allocated fund that a district utilized by the end of 2013.

Through the interaction of fund utilization and Post (equation 7), Column (1)-(2) in Table 10, show that fund utilization is not associated with any significant impact on credit after the regulation. We also categorize all districts above the median level of fund utilization as high treatment districts and below median as low treatment districts. Column (3)-(4) show that the result is insignificant in this specification also. Together , these results rule out the implementation intensity as the reason for credit decline in the treated districts.

6 Robustness

6.1 Controlling for COVID-19

Our sample runs from 2015 to 2023, which includes the COVID-19 pandemic. If the pandemic hit NCAP-designated districts systematically harder, our estimates could conflate the effects of NCAP and COVID. Appendix Table A6 addresses this by adding a *High COVID* indicator, built from Google Mobility data, to equation (1); it equals one if workplace mobility

fell in a district during 2020 and 2021, and zero otherwise. Column (1) shows that high-COVID districts did experience lower credit, with a coefficient of -0.088 on *High COVID* $\times$ *Post*. Column (2) adds the NCAP treatment: the *Treated* $\times$ *Post* effect remains large and significant at -0.142, while the triple interaction *Treated* $\times$ *Post* $\times$ *High COVID* is insignificant, so COVID does not differentially explain the credit decline in treated districts. Columns (3)–(5) repeat the exercise for the sub-components of credit and reproduce our main pattern: industrial credit falls and agricultural credit rises in treated districts, with no effect on personal credit, even after controlling for COVID. Together, these results rule out the pandemic as an alternative explanation.

6.2 Neighboring and Non-Neighboring Control Groups

One of issues with using all Non-NCAP designated districts as control is the that many of these districts are not comparable to NCAP designated districts. To test if our results are robust to using more comparable control group, we use only neighboring districts of the treated districts as our control group. So, we took all districts which share geographical boundary with any treated districts as our control group and re-estimate equation (1). Appendix Table A7 shows that our results stay virtually the same. This is true for total outstanding credit as well as the sub components of total credit.

A related concern is that NCAP could generate spillover effects on credit allocation. In other words, banks may reallocate lending away from treated districts toward geographically proximate non-treated districts, which would bias our main estimates. To address this possibility, we reconstruct our control group using only non-NCAP districts that do not share a geographic border with any treated district. So, we drop all neighboring districts of treated districts from the control group and retain only non-adjacent, non-treated districts, and again estimate equation (1). Appendix Table A8 shows that our main result is virtually unchanged, and the same holds for the sub-components of total credit.

These results confirm that the main estimates are not sensitive to the composition of the control group and are not driven by spatial spillovers.

7 Conclusion and Policy implications

We show that India's National Clean Air Programme (NCAP), a broad, aspirational environmental policy with no market mechanism and weak enforcement machinery, produced a large and persistent reallocation of bank credit away from the regulated districts. Outstanding bank credit fell by roughly 10 percent in non-attainment districts relative to control districts, mostly concentrated in industrial lending, even as measured air quality improved by less than 2 percent. New investment fell by 16 percent over the same period.

Multiple pieces of evidence identify firm demand as the source of this reallocation rather than bank supply or regulatory enforcement. First, the decline in credit is associated with a decline in environmental clearances sought by firms, not clearances granted by regulators, indicating that firms are seeking fewer polluting projects rather than being refused permits. Second, a Khwaja and Mian (2008)-style test on firm-bank-year data shows that banks with greater pre-policy exposure to treated districts did not curtail lending after NCAP, even to polluting firms. Textual analysis of Banks' annual report also supports the same hypothesis. Third, polluting firms cut capital expenditure and borrowing in treated districts by more than five percentage points relative to green firms and shifted this activity to untreated districts. Moreover, their annual reports show a significant increase in uncertain and litigious language around air pollution after 2019. Finally, the effect is unrelated to how vigorously each district implemented the programme, ruling out enforcement intensity as the driver. Together, these results point to the single mechanism that firms are deferring and relocating investment rather than committing capital to districts which are regulated under NCAP due to increased regulatory risk.

These findings have several implications. First, even aspirational environmental announcements can have large financial market consequences through the expectation channel, a mechanism that has received relatively little attention in the environmental finance literature. Second, spatial reallocation is a primary adaptation strategy for firms in developing economies that lack market-based environmental risk hedging tools, extending the regulatory arbitrage literature to credit markets. Third, vaguely defined regulations may impose economic costs through uncertainty without delivering commensurate environmental benefits, pointing to the importance of policy design clarity.

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Figure 1: **Parallel Trend plot**
This figure plots the event-study estimates of the effect of the National Clean Air Programme (NCAP) on the log of outstanding bank credit. Coefficients are estimated from a specification with district and year fixed effects, and the vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

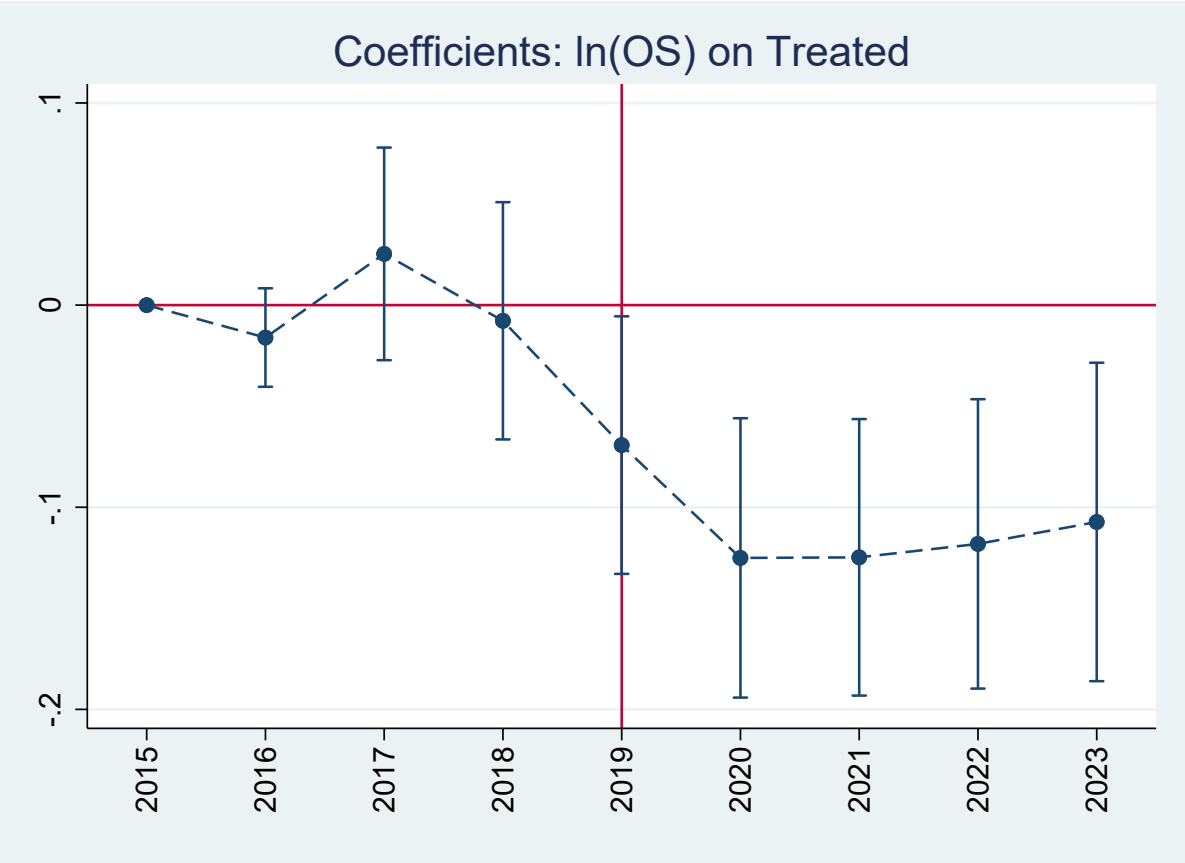


TABLE 1: **Summary Statistics**
This table reports summary statistics for the main variables used in the empirical analysis.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Panel A: District-Year					
$PM_{2.5}$ ($\mu g/m^3$)	5,580	48.52	18.33	18.72	132.17
Total Bank Credit (Rs. Million)	6,072	137,786.54	743,374.82	10.20	22,706,716.70
Agriculture Share	6,067	0.32	0.19	0.00	1.00
Industry Share	6,064	0.12	0.11	0.00	0.78
Personal Loans Share	6,071	0.36	0.17	0.00	1.00
Other Credit Share	5,802	0.20	0.08	0.03	0.81
Credit Limit (Rs. Million)	4,926	210,553.1	1,300,250.00	43.2	32,468,740
Credit Limit used (%)	4,926	0.76	0.08	0.05	1.62
Environmental Clearances Sought	5,364	1.20	5.50	0.00	299.00
Environmental Clearances Received	5,364	0.90	5.10	0.00	242.00
New Investment (Rs. Million)	4,454	31,685.46	160,781.24	10.00	6,643,250.00
Average Workplace Mobility Change (%)	4,905	-14.15	8.17	-50.00	13.06
City NCAP Fund Utilization (%)	612	50.94	34.18	0.00	100.00
Bank Exposure to Treated Districts	2,634	0.55	0.44	0.00002	1.00
Panel B: Firm-district-Year CapeEx					
Capital expenditure (Rs. Million)	65,210	9860.902	59243.20	1.60	5000100.00
Brown	31,769	.662	.473	0	1
Panel C: Firm-district-Year Credit					
Credit (Rs. Million)	258,637	396	1520	0.45	12,000
Brown	182,839	.037	.189	0	1
Panel D: Firm-bank-Year Credit					
Credit (Rs. Million)	219,902	439	1620	0.45	12,500
Brown	91,727	.048	.212	0	1
Panel E: Loan level interest rate					
Interest rate	59,690	10.09	2.49	5	25
Brown	59,690	0.757	0.428	0.00	1
Panel E: Firm-Year Annual Reports					
Air Pollution Mentions (count)	17,162	15.68	32.74	0	796.00
Risk Words in AP Context (%)	12,294	1.43	1.68	0.00	19.05

TABLE 2: **Main results**

This table reports estimates of the Difference-in-Difference specification as per Equation 1. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations. Dependent variable in column (1) is log value of PM2.5 reading, column (2) is Log of total outstanding credit in a district, column (3) is percentage of Industrial credit in total credit, column (4) is percentage of Agricultural credit in total credit, column (5) is percentage of Personal credit in total credit. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(PM2.5)	(2) ln(Credit)	(3) Industrial Credit (%)	(4) Agricultural Credit (%)	(5) Personal Credit (%)
Treated × Post	-0.019**	-0.103***	-0.023***	0.027***	0.000
	(0.009)	(0.023)	(0.006)	(0.005)	(0.005)
Observations	5580	6055	6046	6049	6054
R-squared	0.96	0.98	0.86	0.94	0.93
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

TABLE 3: **Mechanism: New Investment**

This table reports estimates examining the mechanism through which the National Clean Air Programme (NCAP) affects bank credit. *Treated* is one for non-attainment districts and zero otherwise. *Post* is one from Year 2019 onward and zero otherwise. Column (1) estimates the impact of NCAP on log new investment as per Equation 1. Column (2) examines whether the effect of NCAP on log outstanding credit varies with lagged investment as per Equation 2. The sample consists of district-year observations. Standard errors are clustered at the district level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)
	ln New Investment	ln(Credit)
Treated × Post	-0.163*	-0.186**
	(0.106)	(0.099)
Lag Investment		0.012***
		(0.004)
Treated × Lag Investment		-0.014
		(0.010)
Post × Lag Investment		-0.016***
		(0.005)
Treated × Post × Lag Investment		0.018*
		(0.011)
Observations	4,377	3,649
R-squared	0.54	0.99
District FE	Yes	Yes
Year FE	Yes	Yes

TABLE 4: **Mechanism: Environmental Clearances**

This table reports estimates examining whether changes in environmental clearances explain the effect of NCAP on bank credit. *Treated* is one for non-attainment districts and zero otherwise. *Post* is one from Year 2019 onward and zero otherwise. Columns (1) and (3) estimate the effect of NCAP on the number of environmental clearances sought and received, respectively, using Poisson pseudo-maximum likelihood, as per Equation 1. Columns (2) and (4) examine whether the effect of NCAP on log outstanding credit varies with environmental clearances sought and received, respectively, as per Equation 2. The sample consists of district-year observations. Standard errors are clustered at the district level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) Clearances Sought	(2) ln(Credit)	(3) Clearances Received	(4) ln(Credit)
Treated × Post	-0.118*	-0.075**	-0.213***	-0.068**
	(0.074)	(0.030)	(0.076)	(0.030)
Clearance Sought		0.013**		
		(0.006)		
Treated × Clearance Sought		-0.009		
		(0.008)		
Post × Clearance Sought		-0.014*		
		(0.007)		
Treated × Post × Clearance Sought		0.015*		
		(0.009)		
Clearance Received				0.005
				(0.009)
Treated × Clearance Received				-0.003
				(0.011)
Post × Clearance Received				-0.012
				(0.010)
Treated × Post × Clearance Received				0.010
				(0.012)
Observations	5,301	4,896	4,518	4,896
Pseudo R^2 / R^2	0.38	0.99	0.37	0.99
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

TABLE 5: **Brown Firms CapEx relocation:** This table reports estimates of the impact of NCAP on Capital Expenditure by polluting versus non-polluting firms as per Equation 4. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. *Brown* is a dummy variable that takes value one for polluting firms and zero otherwise. Sample has Firm-District-Year observations. Dependent variable in column 1 and 2 is log of Investment, column 3 and 4 is *Investment dummy* that takes a value 1 if a firm makes any investment and zero otherwise. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
	ln(investment)	ln(investment)	investment dummy	investment dummy
Treated	0.156***		0.022***	
	(0.023)		(0.003)	
Treated × Post	-0.048**	-0.050**	-0.007**	-0.007**
	(0.023)	(0.023)	(0.003)	(0.003)
Brown	-0.091***	-0.089***	-0.013***	-0.013***
	(0.021)	(0.020)	(0.003)	(0.003)
Treated × Brown	0.112***	0.111***	0.013***	0.013***
	(0.025)	(0.026)	(0.003)	(0.003)
Post × Brown	0.027	0.028	0.004	0.004
	(0.022)	(0.021)	(0.003)	(0.003)
Treated × Post × Brown	-0.052**	-0.051**	-0.005*	-0.005*
	(0.026)	(0.026)	(0.003)	(0.003)
Observations	559188	559188	559188	559188
R-squared	0.55	0.56	0.60	0.60
District FE	No	Yes	No	Yes
Firm × Year FE	Yes	Yes	Yes	Yes

TABLE 6: **Credit relocation:**
This table reports estimates of the impact of NCAP on credit allocation to polluting versus non polluting firms as per Equation 4. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. *Brown* is a dummy variable that takes value one for polluting firms and zero otherwise. Sample has Firm-District-Year observations. Dependent variable in column 1 and 2 is log of Investment, column 3 and 4 is *credit dummy* that takes a value 1 if a firm gets any credit and zero otherwise. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(credit)	(2) ln(credit)	(3) credit dummy	(4) credit dummy
Treated	0.807***		0.044***	
	(0.246)		(0.013)	
Treated × Post	-0.214	-0.214	-0.009	-0.009
	(0.391)	(0.391)	(0.023)	(0.023)
Treated × Brown	1.209**	1.174***	0.063**	0.061***
	(0.484)	(0.433)	(0.026)	(0.023)
Treated × Post × Brown	-0.536**	-0.536**	-0.029**	-0.029**
	(0.249)	(0.249)	(0.013)	(0.013)
Observations	1,412,154	1,412,154	1,412,154	1,412,154
R-squared	0.38	0.39	0.39	0.40
District FE	No	Yes	No	Yes
Firm × Year FE	Yes	Yes	Yes	Yes

TABLE 7: **Supply side test:**
This table reports lending by bank with different degree of pre-policy exposure, as per Equation 5. *Post* is one from Year 2019 onward and zero for Years before that. *Exposure* is a continuous variable that represents the pre-policy exposure of a bank to treated districts. Sample has Firm-Bank-Year observations. Dependent variable in column 1 and 2 is log of credit, column 3 and 4 is *credit dummy* that takes a value 1 if a firm gets any credit and zero otherwise. Standard errors are clustered at the lender level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(credit)	(2) ln(credit)	(3) credit dummy	(4) credit dummy
Post × Exposure	-0.022	-0.022	0.002	0.002
	(0.566)	(0.566)	(0.034)	(0.034)
Observations	858,492	858,492	858,492	858,492
R-squared	0.35	0.40	0.35	0.41
Firm × Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No
Firm × Bank FE	No	Yes	No	Yes

TABLE 8: **Interest rate:**
This table reports estimates of the impact of NCAP on interest rate charged on credit. Empirical specification for column (1)-(3) and column (4)-(5) are similar to Equation 3 and Equation 4 respectively with different sets of fixed effects. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. *Brown* is a dummy variable that takes value one for polluting firms and zero otherwise. Sample is a pooled cross-section of interest rate charged on loans to firms across year 2015–2023. Dependent variable in column (1)-(3) is interest rate charged on all firms, Brown firms, and Green firms respectively. Column (4)-(5) has interest rate as dependent variable for full sample. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Interest rate				
	(1)	(2)	(3)	(4)	(5)
	All Sample	Brown Subsample	Green Subsample	Interest rate	Interest rate
Treated × Post	0.104	0.145	-0.034	0.003	-0.055
	(0.156)	(0.163)	(0.202)	(0.191)	(0.181)
Brown				0.248**	
				(0.100)	
Treated × Brown				-0.255**	-0.305***
				(0.120)	(0.108)
Post × Brown				-0.158	
				(0.130)	
Treated × Post × Brown				0.151	0.157
				(0.149)	(0.142)
Observations	58,718	44,411	14,109	58,718	58,709
Adjusted R^2	0.50	0.49	0.54	0.49	0.50
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
Industry FE	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	No	No	No	Yes

TABLE 9: **Air Pollution Discussion in Annual Reports**

This table reports estimates of the effect of the NCAP regulation on the discussion of Air Pollution (AP) in annual reports as per Equation 6. Columns (1) and (2) use a sample of polluting firms, while Columns (3) and (4) use a sample of lending institutions. The dependent variable is the number of air pollution mentions in Columns (1) and (3), and the number of risk-related words appearing in the context of air pollution mentions in Columns (2) and (4). *Post* equals one for FY 2019–20 onward and zero otherwise. Standard errors are clustered at the firm level and reported in parentheses. Risk words are defined using the Litigious and Uncertainty categories from the Loughran–McDonald dictionary. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Polluting Firms		Lending Institutions	
	(1)	(2)	(3)	(4)
	AP Mentions	Risk Words in AP Context	AP Mentions	Risk Words in AP Context
Polluting × Post	7.603***	0.163**		
	(4.70)	(2.05)		
Lender × Post			-0.003	-0.200
			(-0.00)	(-1.13)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,911	11,379	15,911	11,379
R-squared	0.646	0.603	0.643	0.602

TABLE 10: **Fund utilization in treated districts**

This table reports the impact of regulatory implementation intensity in treated districts as per Equation 7. Here, *City Utilization* is a continuous variable representing the percent of NCAP fund utilized by a district. *High Treatment* is a dummy variable with value one for districts with above median level of fund utilization and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations for NCAP designated districts. Dependent variable in column 1 and 3 is Log of total outstanding credit in a district, column 2 and 4 is percentage of Industrial credit in total credit. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(Credit)	(2) Industrial credit (%)	(3) ln(Credit)	(4) Industrial credit (%)
Post × City Utilization	-0.000	0.000		
	(0.001)	(0.000)		
High Treatment × Post			-0.001	-0.004
			(0.042)	(0.011)
Observations	542	542	942	942
R-squared	0.97	0.89	0.97	0.88
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Appendix

Figure A1: **Air Pollution Mentions by Treatment Status**
This figure plots the average number of air-pollution mentions in the annual reports of polluting (treated) versus other firms around the introduction of the National Clean Air Programme (NCAP).

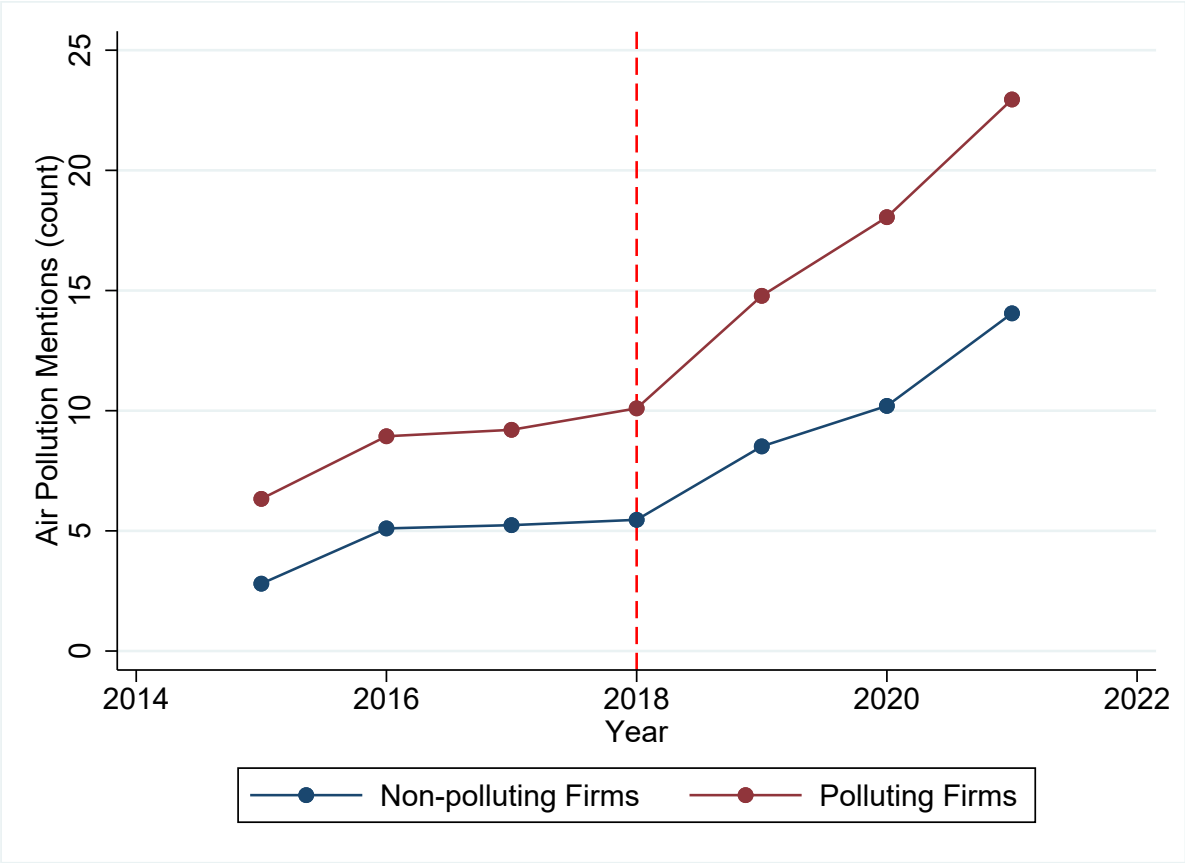


TABLE A1: **Variable Definitions**

Variable	Definition	Source
Panel A: Treatment, Timing, and Firm Type		
Treated	Equals one if the district contains an NCAP-designated non-attainment city, and zero otherwise.	CPCB
Post	Equals one for the post-NCAP period (calendar years 2019 onward for district data; fiscal year 2019–20 onward for firm and text data).	—
Brown (Polluting)	Equals one if the firm operates in a polluting sector, using the IPCC brown/green classification hand-mapped to CMIE/Prowess industry names.	IPCC; CapexDx
Lender	Equals one if the firm is a lending institution (bank, NBFC, or housing-finance company), identified from company names.	Prowess
Panel B: District-Level Variables		
Outstanding Credit	Total outstanding bank credit of scheduled commercial banks in a district-year (Rs. million); entered in logs.	CMIE SoI
Industrial Credit (%)	Industrial credit as a share of total outstanding credit in a district-year.	CMIE SoI
Agricultural Credit (%)	Agricultural credit as a share of total outstanding credit.	CMIE SoI
Personal Credit (%)	Personal loans as a share of total outstanding credit.	CMIE SoI
New Investment	Value of newly announced capital-expenditure projects in a district-year (Rs. million); entered in logs.	CapexDx
PM2.5	Annual average fine-particulate (PM2.5) concentration in a district ($\mu g/m^3$); entered in logs.	Kawano et al. (2025)
Panel C: Firm-Level Variables		
Investment	Capital expenditure by a firm in a given district and year (Rs. million); entered in logs.	CapexDx
Investment Dummy	Equals one if the firm undertakes any investment in a district-year.	CapexDx
Credit	New borrowing by a firm in a given district and year (Rs. million); entered in logs.	MCA IoC
Credit Dummy	Equals one if the firm receives any credit in a district-year.	MCA IoC
Clearances Sought	Number of environmental clearances applied for in a district-year.	CapexDx

Continued on next page

Variable Definitions (continued)

Variable	Definition	Source
Clearances Received	Number of environmental clearances granted in a district-year.	CapexDx
Panel D: Bank-Level Variable		
Exposure	Share of a bank's total lending over 2008–2018 directed to treated districts (pre-policy exposure to NCAP districts).	MCA IoC
Panel E: Regulation Intensity and Controls		
Fund Utilization	Percentage of allocated NCAP funds a district had utilized; proxy for implementation intensity.	CPCB Prana
High Treatment	Equals one for districts with above-median NCAP fund utilization.	CPCB Prana
High COVID Impact	Equals one if a district's average change in workplace mobility over 2020–2021 was negative.	Google Mobility
Panel F: Annual-Report Text Variables		
Air Pollution Mentions	Count of air-pollution / NCAP-related terms in a firm's annual report (firm-year).	Prime Infobase
Risk Words in AP Context (%)	Share of words within a ±10-word window of an air-pollution mention that fall in the LM Litigious or Uncertainty categories.	Prime Infobase; LM
Mentions Air Pollution	Equals one if the annual report contains at least one air-pollution mention.	Prime Infobase

Notes: CMIE SoI = CMIE States of India; CapexDx = CMIE CapEx database; MCA IoC = Ministry of Corporate Affairs Index of Charges; CPCB = Central Pollution Control Board; LM = Loughran–McDonald financial sentiment dictionary. Indicator variables take the value one when the stated condition holds and zero otherwise.

TABLE A2: **Summary Statistics for Pre-treatment period**
This table reports summary statistics for the main variables used in the analysis separately for treated and control districts in the Pre-treatment period. Treated districts are those designated as non-attainment districts under the National Clean Air Programme (NCAP). The table reports the number of observations, mean, median, standard deviation, and the p-value from a test of equality of means between treated and control districts.

Variable	Group	Obs.	Mean	Median	Std. Dev.	p-value (Difference in Means)
Log(Credit Outstanding)	Treated	397	11.748	11.537	1.348	0.000
	Control	2105	9.735	9.913	1.488	
Agriculture Share	Treated	397	0.206	0.181	0.154	0.000
	Control	2104	0.385	0.399	0.199	
Industry Share	Treated	397	0.241	0.217	0.131	0.000
	Control	2101	0.114	0.076	0.115	
Personal Loans Share	Treated	397	0.294	0.288	0.104	0.149
	Control	2104	0.307	0.264	0.168	
Environment clearance Received	Treated	444	1.493	1.000	2.711	0.000
	Control	1940	0.379	0.000	1.178	
Environment clearance Sought	Treated	444	2.507	1.000	3.640	0.000
	Control	1940	0.816	0.000	2.816	
Log(new investment)	Treated	430	9.590	9.586	1.777	0.000
	Control	1533	7.826	7.935	2.038	
Workplace Mobility Change	Treated	384	-19.029	-18.302	8.295	0.000
	Control	1796	-13.106	-12.945	7.755	
log(PM2.5 AQI)	Treated	420	3.945	3.871	0.301	0.000
	Control	2060	3.856	3.848	0.386	

TABLE A3: **Firms CapEx relocation**

This table reports estimates of the impact of NCAP on Capital Expenditure by firms as per Equation 3. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has Firm-District-Year observations. Dependent variable in column 1 and 2 is log of Investment, column 3 and 4 is *Investment dummy* that takes a value 1 if a firm makes any investment and zero otherwise. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(investment)	(2) ln(investment)	(3) investment dummy	(4) investment dummy
Treated	0.188***		0.025***	
	(0.022)		(0.003)	
Treated × Post	-0.075***	-0.076***	-0.010***	-0.010***
	(0.021)	(0.020)	(0.003)	(0.003)
Observations	483813	483813	483813	483813
R-squared	0.55	0.55	0.59	0.59
District FE	No	Yes	No	Yes
Firm × Year FE	Yes	Yes	Yes	Yes

TABLE A4: **Supply side test:**
This table reports lending to polluting versus non polluting firms by bank with different degree of pre-policy exposure, as per Equation 5 interacted with *Brown*. *Post* is one from Year 2019 onward and zero for Years before that. *Exposure* is a continuous variable that represents the pre-policy exposure of a bank to treated districts. *Brown* is a dummy variable that takes value one for polluting firms and zero otherwise. Sample has Firm-Bank-Year observations. Dependent variable in column 1 and 2 is log of credit, column 3 and 4 is *credit dummy* that takes a value 1 if a firm gets any credit and zero otherwise. Standard errors are clustered at the lender level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(Credit)	(2) ln(Credit)	(3) Credit dummy	(4) Credit dummy
Post × Exposure	0.002	0.002	0.004	0.004
	(0.579)	(0.579)	(0.035)	(0.035)
Brown × Exposure	0.511*		0.032**	
	(0.271)		(0.016)	
Post × Brown × Exposure	-0.182	-0.182	-0.015	-0.015
	(0.265)	(0.265)	(0.015)	(0.015)
Observations	858492	858492	858492	858492
R-squared	0.35	0.40	0.35	0.41
Firm × Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No
Firm × Bank FE	No	Yes	No	Yes

TABLE A5: **Supply side test: Credit Limit**

This table reports estimates of the impact of NCAP on credit limit utilization in districts, using Equation 1 augmented with a *High capacity* × *Post* interaction. Here, *High capacity* is a dummy variable which takes value one for districts which have below median level of credit limit utilization. It takes the value zero otherwise. *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations. Dependent variable in column 1 is the percentage of credit limit that has been borrowed. This column covers the full sample. Column 2 and 3 also have the same dependent variable, but for sub samples of NCAP (Treated) and Non-NCAP (Control) districts respectively. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	Borrowing (%)		
	(1)	(2)	(3)
	Full sample	NCAP districts	Control districts
Post × high capacity	0.039***	0.011	0.039***
	(0.006)	(0.007)	(0.006)
Post × Treated	0.003		
	(0.005)		
Post × high capacity × Treated	-0.028***		
	(0.009)		
Observations	4856	842	4014
R-squared	0.65	0.70	0.61
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

TABLE A6: **Controlling for Covid 19**

This table reports estimates of the impact of NCAP after controlling for Covid 19 pandemic, using Equation 1 augmented with a *High covid impact* × *Post* interaction. Here, *High covid impact* is a dummy variable which takes value one for districts where the change in workplace commute was negative for Year 2020 and 2021. It takes the value zero otherwise. *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations. Dependent variable in column 1 and 2 is Log of total outstanding credit in a district, column 3 is percentage of Industrial credit in total credit, column 4 is percentage of Agricultural credit in total credit, column 5 is percentage of Personal credit in total credit. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1) ln(Credit)	(2) ln(Credit)	(3) Industrial Credit (%)	(4) Agricultural Credit (%)	(5) Personal Credit (%)
High covid impact × Post	-0.088***	-0.086***	0.002	-0.006	-0.005
	(0.025)	(0.027)	(0.005)	(0.006)	(0.005)
Treated × Post		-0.142***	-0.024***	0.029***	-0.002
		(0.045)	(0.006)	(0.005)	(0.005)
Treated × Post × High covid impact		0.050			
		(0.053)			
Observations	6055	6055	6046	6049	6054
R-squared	0.98	0.98	0.84	0.93	
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

TABLE A7: **Neighboring districts as control group**

This table reports estimates of NCAP, as per Equation 1, on the restricted sample with only neighboring districts of NCAP districts as control. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations. Dependent variable in column 1 is Log of total outstanding credit in a district, column 2 is percentage of Industrial credit in total credit, column 3 is percentage of Agricultural credit in total credit, column 4 is percentage of Personal credit in total credit. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
	ln(Credit)	Industrial credit (%)	Agricultutral credit (%)	Personal credit (%)
Treated × Post	-0.092***	-0.025***	0.033***	-0.003
	(0.027)	(0.006)	(0.006)	(0.005)
Observations	3468	3468	3468	3468
R-squared	0.97	0.87	0.93	0.89
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

TABLE A8: **Non-neighboring districts as control group**

This table reports estimates of NCAP, as per Equation 1, on the restricted sample with only non-neighboring districts of NCAP districts as control. Here, *Treated* is one for Non attainment district and zero otherwise. *Post* is one from Year 2019 onward and zero for Years before that. Sample has District-Year observations. Dependent variable in column 1 is Log of total outstanding credit in a district, column 2 is percentage of Industrial credit in total credit, column 3 is percentage of Agricultural credit in total credit, column 4 is percentage of Personal credit in total credit. Standard errors are clustered at the district level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	(1)	(2)	(3)	(4)
	ln(Credit)	Industrial credit (%)	Agricultural credit (%)	Personal credit (%)
Treated × Post	-0.126***	-0.021***	0.024***	-0.002
	(0.028)	(0.006)	(0.006)	(0.006)
Observations	3529	3520	3523	3528
R-squared	0.99	0.84	0.93	0.92
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes